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Highlights

- A closed-loop supply chain with remanufacturing lead time variability is analysed
- Through simulation, the dynamic performance is assessed under a variety of scenarios
- Different levels of information transparency are considered
- The variability of remanufacturing lead times seriously damage the dynamic behaviour
- Managerial implications are discussed

On the Dynamics of Closed-Loop Supply Chains under Remanufacturing Lead Time Variability

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Abstract: Remanufacturing practices in closed-loop supply chains (CLSCs) are often characterised by highly variable lead times due to the uncertain quality of returns. However, the impact of such variability on the dynamic benefits derived from adopting circular economy models remains largely unknown in the closed-loop literature. To fill the gap, this work analyses the Bullwhip and inventory performance of a multi-echelon CLSC with variable remanufacturing lead times under different scenarios of return rate and information transparency in the remanufacturing process. Our results reveal that ignoring such variability generally leads to an overestimation of the dynamic performance of CLSCs. We observe that enabling information transparency generally reduces order and inventory variability, but it may have negative effects on average inventory if the duration of the remanufacturing process is highly variable. Our findings result in useful and innovative recommendations for companies wishing to mitigate the negative consequences of lead time variability in CLSCs.

Keywords: Bullwhip effect; closed-loop supply chains; inventory control; lead time variability; remanufacturing; supply chain dynamics.

1 INTRODUCTION

1.1 Context

With the advent of environmental concerns and the pursuit of the Circular Economy (World Economic Forum, 2016), the Operations and Supply Chain (SC) Management discipline is undergoing an epochal revolution. This springs from the embracing of new business models that encourage practitioners to design for re-use, to collect used products, and to restore them to a usable state, which represents a departure from traditional production and consumption systems (Genovese et al. 2017). In a sense, the linear 'take-make-dispose' model is increasingly unfit for the reality within which it operates (United Nations 2015); and, therefore, the establishment of Circular Economy systems becomes a critical requirement of modern societies in both developed and developing countries (Heydari et al. 2017). Accordingly, the European Commission aims to triple the value of Europe's remanufacturing sector by 2030 up to €100 billion (European Remanufacturing Council 2017), while in the US remanufacturing operations are already supporting at least 180,000 full-time jobs (Abbey and Guide 2018). All in all, we may conclude that the Circular Economy is undoubtedly one the most relevant challenges for policy makers nowadays all around the world, and it will continue capturing the attention and efforts of practitioners and researchers during the next decade (Korhonen et al. 2018, Goltsos et al. 2018).

A strategic driver of the Circular Economy is irrefutably the Closed-Loop Supply Chain (CLSC), a logistics structure that simultaneously considers forward and reverse SC operations (Batista et al. 2018). The main duties of a CLSC are twofold: first, it is responsible for value-added processes aimed at satisfying customers' demands (as in a traditional, open-loop, SC); and second, it needs to collect the end-of-lifecycle products from customers and determine the best ways to recover their value (Govindan and Soleimani 2017). The growing relevance of the CLSC model (Mota et al. 2018) has captured the interest of different research communities in the last decade. However, the majority of the CLSC literature is devoted to the design and optimisation of the SC structure. As pointed out by recent reviews of the literature (Cannella et al. 2016, Braz et al. 2018, Goltsos et al. 2018, Hosoda and Disney 2018), relatively little research has focused on the dynamics of such systems, *i.e.* the time-varying interactions of the different elements in the SC (such as inventory policies, forecasting procedures, and lead times) by analysing the evolution of the flows that define its response (mainly, materials and information). Such research should encompass an in-depth understanding of the Bullwhip Effect (Lee et al. 1997, Chen et al. 2000), *i.e.* the magnification of order oscillations as one moves up the SC from the consumer to the suppliers (Croson and Donohue 2005), together with an exhaustive study of the SC inventory performance (Disney and Lambrecht 2008, Ponte et al. 2017). Over the years, evidence has suggested that Bullwhip- and inventory-related costs are strongly interrelated and play a pivotal role in many businesses (Metters 1997, Wang and Disney 2016).

1.2 Background

The first insights on the relationship between CLSC and Bullwhip Effect date back to 15 years ago, when Tang and Naim (2004) observed that CLSCs can operate with a reduced order variability as compared to the open-loop form. Since then, some studies have contributed to understanding how CLSCs should be managed for effectively integrating the forward and reverse flows of materials to mitigate the detrimental consequences of order and inventory variabilities under different modelling assumptions. Particularly, most of the research efforts have focused on the impact of three features of the CLSC setting, namely, (1) volume of the returns, (2) duration of the reverse logistics operations, and (3) transparency of information.

The first feature has been mainly addressed through the return rate. In this regard, the majority of studies found that increasing the return rate results in a decreased Bullwhip Effect (see *e.g.* Tang and Naim 2004, Zhou and Disney 2006, Wang and Ding 2009, Pati et al. 2010, Adenso-Díaz et al. 2012, Turrisi et al. 2013, Cannella et al. 2016, Dev et al. 2017, Zhou et al. 2017). This suggests that CLSCs experience lower Bullwhip Effect than traditional SCs (in which the return rate is 0). However, Hosoda et al. (2015) concluded that CLSCs are more likely to suffer from this dynamic phenomenon given the presence of two different sources of uncertainties (demand and returns). In terms of inventory variability, depending on the modelling conditions, increasing the return rate may help to improve the performance (see *e.g.* Zhou and Disney 2006, Cannella et al. 2016) or not (see *e.g.* Turrisi et al. 2013). The second feature, *i.e.* the duration of the reverse logistics operations, has been mainly explored through the remanufacturing lead time. In this regard, some authors showed the dynamic benefits derived from shortening remanufacturing lead times (see *e.g.* Zhou and Disney 2006, Tang and Naim 2004, Huang and Liu 2008, Cannella et al. 2016, Zhou et al. 2017). At the same time, interestingly, some studies observed that the dynamics of CLSCs may benefit from longer remanufacturing lead times. This has been labelled as a 'lead-time paradox' —since lead times are known to have a strong negative impact on the performance of traditional SCs, see *e.g.* Fang (2013), Ponte et al. (2018)—, and was in-depth analysed by Hosoda and Disney (2018). When it comes to the third feature, several information sharing structures have been proposed in the closed-loop literature. In general terms, there is a wide consensus on the benefits of transparency of information in CLSC settings, both in terms of Bullwhip Effect and inventory variability (see *e.g.* Tang and Naim 2004, Hosoda et al. 2015, Cannella et al. 2016).

1.3 Problem statement and research motivation

All in all, the above review of the relevant body of knowledge reveals two main aspects. First, the contrasting results on the impact of the key factors, which may be due to various SC scenarios, modelling assumptions, and parameter values (Cannella et al. 2016, Hosoda and Disney 2018, Goltsos et al. 2018). Thus, from a managerial viewpoint, improving the dynamics of CLSC requires an in-depth study of the setting in which it operates. Second, the discipline of CLSC dynamics continue to be an embryonic scientific area, which deserves more research in response to the relevance that the Circular Economy is gaining in the current business scene. Importantly, we highlight the lack of studies in the literature explicitly considering the variability of the remanufacturing processes, which is one of the defining characteristics of real-life CLSCs. Indeed, the processes of collecting and restoring used products generate an extra layer of uncertainty that is not typically faced by forward SC managers, covering the quantity and quality of the returns (Guide and Van Wassenhove 2001, Amin and Zhang 2017, Abbey and Guide 2018, Goltsos et al. 2018). This is not only related to the products collected from the market, but also disassembly operations, which can be very expensive, may also damage the parts and render them inoperable (Diallo et al. 2017). The differences in the quality of returns generally translates into highly variable processing times. For instance, quality variations may result in a difference of 300% in the recovery time at IBM's remanufacturing facilities (Denizel and Ferguson 2010). Similar issues related to the uncertain quality of returns and the variable nature of lead times can be found in many other remanufacturing industries, such as the cell phone or automobile industries (Giri and Sharma 2016, Heydari et al. 2018). Essentially, not all used parts need to follow the same route of operations or work centres (Korugan et al. 2013). In this regard, it is known that ignoring such quality uncertainty may result in extensive additional costs, even for low levels of quality variability (Zikopoulos, 2017).

To the best of the authors' knowledge, no prior research has focused on understanding how the variability of remanufacturing lead times alter the dynamic behaviour of CLSCs, which is the main aim of this research work. It should be noted that, while most of the literature on CLSC dynamics assumes deterministic lead times, a few research efforts have modelled stochastic remanufacturing lead times (see *e.g.* Zanoni et al. 2006 and Dev et al. 2017). However, analysing the impact of such variability is out of the scope of these works —rather, they assume a constant value for the standard deviation of the lead time in their experiments. In addition, the potential interactions with other relevant factors, such as the volume of returns, average time length of the reverse logistics operations, and transparency of information, remain unexplored.

1.4 Objective

Motivated by the above mentioned observations, we explore the dynamics of a CLSC characterised by variability in the remanufacturing lead time for different scenarios of return rates, mean lead times, and transparency of information. To this end, we model a serial, three-echelon CLSC in which the recovered products are returned to the downstream echelon, *i.e.* the retailer, via the remanufacturer. This structure emulates common CLSC typologies in the global marketplace (see *e.g.* Abbey and Guide 2018). As examples we can cite traditional SCs that incorporate reverse logistics processes through a third-party remanufacturer (see *e.g.* ReCellular). Also, we can think of CLSCs focused on multiple lifecycle products (see *e.g.* Xerox, Caterpillar and Cummins Diesel), in which it is common that reconditioned products (*i.e.* products restored to its original condition, Gaur et al. 2017) return to the forward flow of materials at the retailer level. Moreover, this structure may represent CLSCs where the return quality is generally good. As highlighted by Zhou et al. (2017), the products returned within the product warranty period often return to the downstream echelons. For example, this is the case of the HP closed-loop cartridge recycling programme, in which approximately 80% of the sold cartridges are returned directly to retailers (Zhou et al. 2017).

In our paper, we attempt to provide comprehensive findings by adopting a full factorial experimental design, similarly to other SC studies (see *e.g.* Evers and Wan 2012, Cannella et al. 2017). In line with the previous discussion, the factors under study are: (1) the mean remanufacturing lead time, (2) the variability of the remanufacturing lead time, (3) the return rate, and (4) the degree of information transparency in the CLSC, *i.e.* the existence, or not, of up-to-date information on the quantity of returns, the remanufacturing lead-time, and the work-in-progress (WIP) level of products being remanufactured. To overcome the complexity and mathematical intractability of the multi-echelon CLSC model under a range of real-life considerations, including lead time variabilities, we adopt a Multi-Agent System (MAS) simulation approach. This is widely recognised as a powerful methodology to perform complex what-if analysis in the SC domain (Long and Zhang 2014). We build on well-established modelling assumptions in the literature of SC dynamics with stochastic lead times and on influential CLSC studies, which provide a benchmark for our work. The performance of the CLSC is measured through three complementary metrics that are commonly adopted in SC dynamics studies; specifically, the order rate variance ratio (Chen et al. 2000), the inventory variance ratio (Disney and Towill 2003), and the average stock (Zipkin 2000).

The rest of the paper is structured as follows: Section 2 describes the CLSC model under consideration; Section 3 defines and justifies the experimental design; Section 4 shows, analyses, and discusses the results obtained; Section 5 reflects on the managerial implications of the previous results; and Section 6 presents the conclusions along with the limitations and directions for future research.

2 CLOSED-LOOP SUPPLY CHAIN MODEL

A well-recognised reference SC laboratory model in SC dynamics studies is that of Chatfield et al. (2004). It consists of a serially-linked SC developed from assumptions based on insights from both axiomatic and empirical research, thus reflecting the actual characteristics of many real-world SCs. Herein, we build on the model and assumptions by Chatfield et al. (2004) and extend them to a CLSC setting in which the reverse flow of materials joins the forward flow at the downstream level. The SC model is implemented on SCOPE, a MAS simulation platform for SC modelling and simulation (Dominguez et al. 2018a).

The CLSC under consideration is represented in Figure 1. Subscript $i = \{1,2,3\}$ indicates the echelon's position in the SC, where $i = 1$ refers to the Manufacturer, $i = 2$ refers to the Distributor, and $i = 3$ refers to the Retailer. In the following paragraphs, we describe and justify the modelling assumptions.

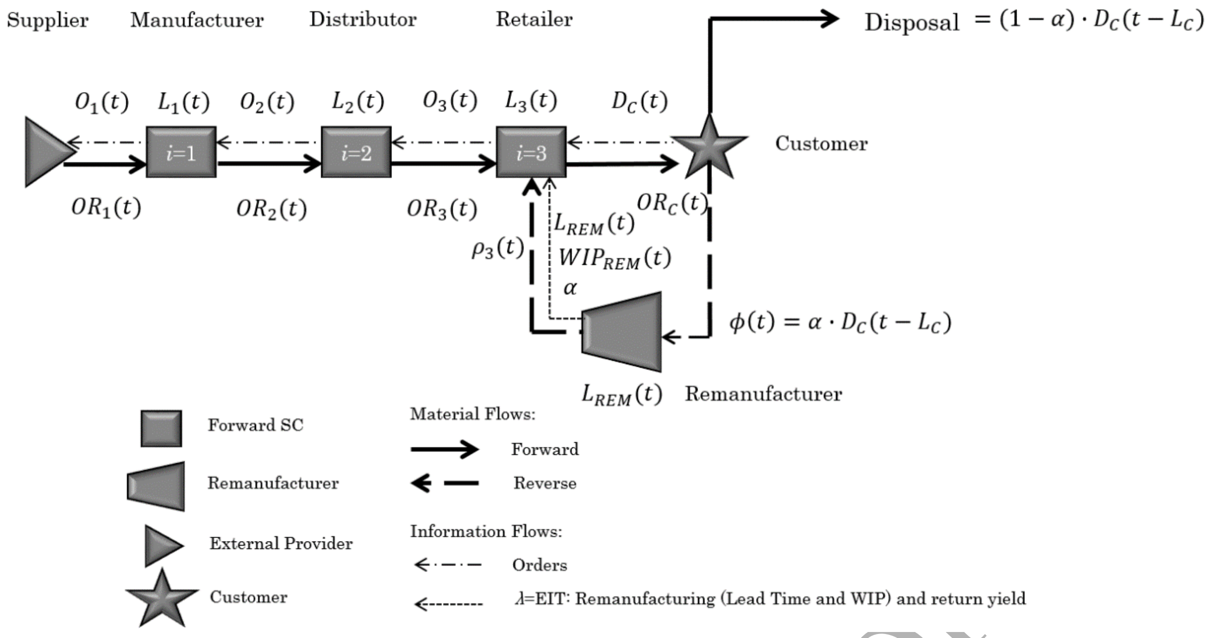


Figure 1. The analysed CLSC with stochastic remanufacturing lead times.

(a) Supply chain configuration. The forward flow of materials defines a single-product serial SC with three echelons (see *e.g.* Cannella et al. 2016, Zhou et al. 2017), namely, Manufacturer, Distributor and Retailer. In addition, we have modelled a reverse flow of materials, which includes the collection and restoring used products by the Remanufacturer. These products are considered to reach an as-good-as-new standard (Zhou et al. 2006), after which they are delivered back to the Retailers' serviceable inventory to meet new demand. We assume unlimited manufacturing, remanufacturing, transportation, and storage capacities (Chatfield et al. 2004, Dejonckheere et al. 2004, Ponte et al. 2018), and that the three SC echelons are allowed to backlog the portion of the demand that cannot be satisfied on time (Chatfield and Pritchard 2013). In addition, the return of excess inventory to upstream partners is not permitted, as usually this is an unrealistic hypothesis that distorts the assessment of SC performance (Chatfield and Pritchard 2013, Dominguez et al. 2015).

(b) Demand and returns. Customer demand at time *t*, denoted by $D_C(t)$, is assumed to be stochastic. We model it as an independent and identically distributed (i.i.d.) random variable following a normal distribution with mean μ_{D_C} and variance $\sigma^2_{D_C}$ (Chatfield et al. 2004, Rekik et al. 2017). Products are assumed to be held by the Customer during L_C periods, representing the consumption lead time. After that, some products return to the SC via the Remanufacturer, while

the others are sent for disposal. The return rate, α, defines the percentage of sold products that return to the SC (after their consumption), $0 \leq \alpha \leq 1$. Therefore, the returns at time t, denoted by $\phi(t)$, are a fraction of customer demand at time $t - L_C$, *i.e.* $\phi(t) = \alpha \cdot D_C(t - L_C)$, see *e.g.* Tang and Naim (2004) and Turrisi et al. (2013). In light of this, we assume that the return volume is proportional to the customer demand, and thus α is a constant, with a delay of L_C (Cannella et al. 2016, Zhou et al. 2017).

(c) Lead times. Lead times in the forward flow of materials are assumed to be stochastic, as happens in most of real-world production and distribution systems (Chatfield et al. 2004). The lead times of the orders issued by the different echelons at time t, denoted by $L_i(t)$ ($i = \{1,2,3\}$), have been modelled as i.i.d. random variables following Gamma distributions with mean μ_{L_i} and variance $\sigma^2_{L_i}$. This assumption is in line with prior research works and industrial data sets (see *e.g.* Chatfield et al. 2004, Kim et al. 2006, Hayya et al. 2011, Bischak et al. 2014). Since we use a periodic-review policy, and thus the simulation model is based on discrete-time windows, lead times are rounded to the nearest integer. In addition, we note that in line with the i.i.d. nature of lead times, order crossovers are allowed to occur in the CLSC. That is, orders may arrive in a different sequence from that in which they were placed (Wang and Disney 2017, Chatfield and Pritchard 2018).

The only lead time in the reverse flow of materials is labelled as remanufacturing lead time, which at time t is denoted by $L_{REM}(t)$. This covers both the lead time required to restore the used product (a processing time) and the lead time required for the product to achieve the serviceable inventory at the Retailer (a transportation time), as in prior works (*e.g.* Tang and Naim 2004, Zhou et al. 2017). Given that the remanufacturer operates according to a push policy (see below), the remanufacturing lead time is the amount of time elapsed between the arrival of returns at the Remanufacturer and the receipt of the remanufactured products by the Retailer. This lead time is also assumed to be stochastic, and it has also been modelled through an i.i.d. random variable following a Gamma distribution with mean $\mu_{L_{REM}}$ and variance $\sigma^2_{L_{REM}}$. We denote by $\rho_3(t)$ the remanufactured products received by the Retailer at time t.

Finally, it should be clarified that although the lead times are formally assigned in the mathematical model when orders are issued by the echelons (for $L_i(t)$, $i = \{1,2,3\}$) and when the returns are received (for $L_{REM}(t)$), we assume that lead times are not known by the relevant nodes until the (re)manufacturing of the specific batch of products has been completed.

(d) Ordering policies. The reverse flow of materials is managed at the Remanufacturer site through a push policy. This means that the used products are processed as soon as they reach the recoverable inventory, which is a common assumption in the CLSC literature (Tang and Naim 2004, Hosoda et al. 2015, Cannella et al. 2016, Zhou et al. 2017).

The forward flow of materials in each echelon is governed by an Order-Up-To (OUT) model, as this family of policies is widely used in real-world SCs (Bischak et al. 2014, Costantino et al. 2015). Therefore, we assume that SC echelons use an adaptive (*R,S*) periodic-review policy (Chatfield et al. 2004, Babai et al. 2016, Syntetos et al. 2016a), where *R* is the review period and *S* is the desired OUT level, which is updated at every period. Orders, which should be non-negative as per the previous assumptions, are placed at discrete time intervals according to the review period as the difference between the OUT level $S_i(t)$ and the inventory position; see Eq. (1). Note that the inventory position is equal to the inventory on-hand, $I_i(t)$, plus the WIP, $WIP_i(t)$, minus the backorders, $B_i(t)$, if any.

$$O_i(t) = \max\{S_i(t) - I_i(t) + B_i(t) - WIP_i(t), \quad 0\} \tag{1}$$

In order to compute the OUT level, we differentiate below between the Retailer, which receives new and remanufactured products, and the upstream members (*i.e.* Distributor and Manufacturer), which only receive new products. In all cases, we model an OUT replenishment rule that do not incorporate order crossover information. This assumption is aligned with previous studies accommodating crossovers (*e.g.* Chatfield and Pritchard 2013) and others concluding that practitioners often ignore the effects of crossovers (*e.g.* Robinson et al. 2001).

(d.1) ***Distributor and Manufacturer***. These nodes compute $S_i(t)$ to allow the system to meet $X_i(t)$, the demand during the protection period $L_i + R$. $S_i(t)$ is then computed as $S_i(t) = \bar{X}_i(t) + z \cdot s_{X_i}(t)$, which includes the normal approximation in

setting the safety stocks (Tyworth and O'Neill 1997, Chatfield et al. 2004). Here, z is a safety factor, while $\bar{X}_i(t)$ and $s_{X_i}(t)$ are the estimations of the mean and the standard deviation of $X_i(t)$ computed at time period t. Following the reasoning of Kim et al. (2006) and Chatfield et al. (2004) for stochastic lead times, $S_i(t)$ is expressed by the common approximation shown in Eq. (2), where $\bar{D}_i(t)$ and $s^2_{D_i}(t)$ are the estimations of the mean and variance of the demand received by echelon i at time t, $\bar{L}_i(t)$ and $s^2_{L_i}(t)$ are the estimations of the mean and variance of lead times in echelon i at time t (the forecast methods used to estimate demand and lead times are provided later in this section). This is a service level-oriented approach (*i.e.* it is assumed that SC nodes are willing to maintain a high service level), which is also very popular in practice (Disney et al. 2016) and has been used in several studies with stochastic lead times (see *e.g.* Chatfield et al. 2004, Chatfield and Pritchard 2018, Dominguez et al. 2018a,b).

$$S_i(t) = (\bar{L}_i(t) + R) \cdot \bar{D}_i(t) + z\sqrt{(\bar{L}_i(t) + R) \cdot s^2_{D_i}(t) + \bar{D}^2_i(t) \cdot s^2_{L_i}(t)}; \quad i = \{1,2\} \tag{2}$$

Note that in this case the WIP is interpreted in a traditional way as the 'inventory on order', that is, the sum of the size of the orders placed but not yet received (see *e.g.* Disney and Lambrecht 2008).

(d.2) ***Retailer***. In this echelon, $S_3(t)$ needs to be computed differently, since there is an incoming flow of restored goods from the Remanufacturer along with that of manufactured goods from the Distributor. Following prior studies (see *e.g.* Tang and Naim 2004, Zhou and Disney 2006, Cannella et al. 2016), the Retailer may calculate $S_3(t)$ using the information available about the remanufacturing process. Specifically, we consider two different information transparency (IT) levels (λ), namely, 'No IT' (referred to as λ=NIT) and 'Enabled IT' (referred to as λ=EIT), which we describe below.

(d.2.1) ***No IT*** **(λ=NIT).** In this scenario, information on the remanufacturing process is not available (Zhou and Disney 2006, Ding and Gan 2009, Adenso-Díaz et al. 2012). Thus, the only information available is the amount of remanufactured products received at each period, $\rho_3(t)$. This quantity automatically increases the Retailer's on-hand inventory. Since the reverse flow is governed by a push policy, the arrival of such products

is not controllable by the Retailer. Hence, the 'net demand' that the Retailer needs to met in each period is $ND_3(t) = D_3(t) - \rho_3(t)$. Following this consideration, $S_3(t)$ can be computed as in Eq. (2) by replacing $D_3(t)$ by $ND_3(t)$; thus $\overline{ND}_3(t)$ and $s^2_{ND_3}(t)$ become the estimations of the mean and variance of the net demand received by the Retailer at time period *t*; see Eq. (3).

$$S_3(t) = (\bar{L}_3(t) + R) \cdot \overline{ND}_3(t) + z\sqrt{(\bar{L}_3(t) + R) \cdot s^2_{ND_3}(t) + \overline{ND}^2_3(t) \cdot s^2_{L_3}(t)} \tag{3}$$

As the remanufacturing process is not observable, the interpretation of the WIP is similar to that discussed for the Manufacturer and Distributor, *i.e.* the WIP only considers the forward flow of materials, like in Tang and Naim's (2004) type-1 and type-2 OUT models for closed-loop settings.

(d.2.2) ***Enabled IT*** ***(λ=EIT).*** Now information on the remanufacturing process is available. As in Tang and Naim's (2004) type-3 model, Cannella et al. (2016) and Zhou et al. (2017), the return rate, the remanufacturing WIP (*i.e.* the amount of returns being processed by the Remanufacturer), and the remanufacturing lead times are assumed to be known by the Retailer. This node uses all this information to improve the estimation of the OUT level. Unlike before, the WIP of the Retailer considers now the forward and reverse pipelines. In other words, it is the sum of the orders placed (upstream) by the Retailer but not yet received plus the returns currently being remanufactured. Consequently, the estimate of the lead time of the WIP needs to consider both the manufacturing and remanufacturing pipelines. Tang and Naim (2004) developed an approximation of the overall lead time (for the case of deterministic lead times) based on the linear combination of both lead times, where the weight of the terms is defined by the return rate α (see also Cannella et al. 2016 and Zhou et al. 2017). In their study, such overall lead time was a fixed parameter. In our model, the forward and the reverse lead times are stochastic variables and, as such, the overall lead time needs to be calculated each period *t*, $L^*_3(t)$, using the most recent information available on both lead times. Replacing $L_3(t)$ by $L^*_3(t)$ in Eq. (2), S^*_3 is computed by

means of Eq. (4), where $\bar{L}_3^*(t)$ and $s_{L_3^*}^2(t)$ are the estimations of the mean average and variance of the overall pipeline lead time at period t.

$$S_3^* = (\bar{L}_3^*(t) + R) \cdot \bar{D}_3(t) + z\sqrt{(\bar{L}_3^*(t) + R) \cdot s_{D_3}^2(t) + \bar{D}_3^2(t) \cdot s_{L_3^*}^2(t)} \tag{4}$$

<u>*(e) Demand and lead times forecast.*</u> We assume that each node dynamically updates the forecast of incoming demand using τ-period moving average/variance techniques (Chatfield et al. 2004, Chen et al. 2000, Syntetos et al. 2016b), as per Eqs. (5) and (6). The forecast of the net demand is updated in a similar way, replacing $D_i(t)$ by $ND_3(t)$ in Eqs. (5) and (6). Meanwhile, the lead times, $L_i(t)$ and $L_3^*(t)$, are estimated through running average/variance approaches (Chatfield 2013), specifically, using all prior information available on the lead times, from t=0 until that of the last batch of products received.

$$\bar{D}_i(t) = \frac{\sum_{k=1}^{\tau} D_i(t-k)}{\tau} \tag{5}$$

$$s_{D_i}^2(t) = \frac{1}{\tau - 1}\sum_{k=1}^{\tau}(D_i(t-k) - \bar{D}_i(t-k))^2 \tag{6}$$

<u>*(f) Sequence of actions.*</u> At the start of period t, the Customer places an order $D_C(t)$ and returns to the Remanufacturer a portion of the previous demand, $\phi(t)$. Then,

- If λ=NIT, the Remanufacturer starts to process the new returns, $\phi(t)$, under a stochastic lead time. In addition, the remanufactured products that have been finalised in this period, $\rho_3(t)$, are received by the Retailer, which immediately increases $I_3(t)$ accordingly.
- If λ=EIT, information on the returns received, $\phi(t)$, is shared with the Retailer, who updates $WIP_3(t)$. Then, the Remanufacturer starts to process the new returns, and the finalised products, $\rho_3(t)$, are received by the Retailer, which therefore increases $I_3(t)$ and reduces $WIP_3(t)$. The lead time of this batch of remanufactured products is shared with the Retailer.

Later, each echelon i, $i = \{1,2,3\}$, performs the following sequence of actions:

i. Determines its OUT level, $S_i(t)$, using the forecasts computed in the previous period;

ii. Places an order $O_i(t)$ and increase $WIP_i(t)$ accordingly, as long as $S_i(t)$ is greater than the actual inventory position;

iii. Receives new products from its upstream partner, $OR_i(t)$, reducing $WIP_i(t)$ and increasing $I_i(t)$ accordingly. Also, if λ=EIT, the Retailer computes the estimation of the overall lead time L_3^* by using the historical information available of the forward and reverse lead times;

iv. Satisfies backorders, if they exist and there is on-hand inventory available (*i.e.* if $B_i(t) > 0$, $I_i(t) > 0$), reducing $I_i(t)$ and $B_i(t)$ accordingly;

v. Receives the new demand from a downstream node, $D_i(t)$. If $D_i(t) \leq I_i(t)$, the demand is completely satisfied (reducing $I_i(t)$ accordingly), with stochastic lead time $L_i(t)$. If $D_i(t) > I_i(t)$, the demand is partially satisfied with the available inventory (reducing $I_i(t)$ accordingly, $I_i(t)$=0), with stochastic lead time, $L_i(t)$. In this case, the unsatisfied demand is backordered, and $B_i(t)$ increases accordingly. If λ=NIT, the Retailer computes $ND_3(t) = D_3(t) - \rho_3(t)$;

vi. Forecasts its demand (or net demand in the case of λ=NIT) $[\bar{D}_i(t), s^2_{D_i}(t); \overline{ND}_3(t), s^2_{ND_3}(t)]$ and lead time (or estimated pipeline lead time in case of λ=EIT) $[\bar{L}_i(t), s^2_{L_i}(t); \bar{L}^*_3, s^2_{L^*_3}]$ for the next period.

3 DESIGN OF EXPERIMENTS

3.1 Experimental factors and model parameters

We employ a full factorial Design of Experiments (DoE) to test the statistical significance of the impact of four experimental factors and their interactions. The factors under consideration are: (1) the mean remanufacturing lead time, $\mu_{L_{REM}}$; (2) the coefficient of variation of the remanufacturing lead-time, $L_{REM}cv = \sigma_{L_{REM}}/\mu_{L_{REM}}$; (3) the return rate, α; and (4) the level of IT on the remanufacturing process, λ.

(1) Due to variations in the condition of returns, the average lead time required for restoring used products may substantially differ between periods (Maiti and Giri 2017, Abbey and Guide 2018, Moshtagh and Taleizadeh 2017, Zikopoulos 2017). In light of this, the mean remanufacturing lead time $\mu_{L_{REM}}$ may be associated with the average quality of the products returned during the period, *i.e.* the better the quality, the lower the average lead time (Korugan et al. 2013, Masoudipour et al. 2017). Thus, by modelling different levels of this factor, we consider different quality scenarios (see *e.g.* Zikopoulos 2017). Specifically, we define three levels for $\mu_{L_{REM}}$ (see Table 1). Note that we consider scenarios where $\mu_{L_{REM}} < \mu_{L_i}$, as it makes sense to assume that remanufacturing requires less time than manufacturing.

(2) The variability of remanufacturing lead times can be related with that in the quality of returns. Note that we consider this variability relative to the mean lead time through the coefficient of variation, denoted by $L_{REM}cv$. We study five levels of this factor. Thus, for a given $\mu_{L_{REM}}$, we explore five levels of $\sigma_{L_{REM}}$, ranging from no variability ($L_{REM}cv = 0$, $\sigma_{L_{REM}} = 0$; *i.e.* the benchmark scenario where the remanufacturing lead time is time-invariant, due to all returns having similar quality) to very high variability ($L_{REM}cv = 1$, $\sigma_{L_{REM}}$=$\mu_{L_{REM}}$, which means that the quality of returns significantly differs from one period to another). The consideration of such a range of scenarios in terms of the variability of the remanufacturing lead time is in line with evidences reported by prior works (see *e.g.* Denizel et al. 2010).

(3) The return rate α is a key factor that allows us to analyse different CLSC scenarios defined by different degrees of circularity, as in previous related studies (see *e.g.* Cannella et al. 2016, Zhou et al. 2017). We consider eight scenarios ranging from low return rates (α=0.1) to high return rates (α=0.8). The results of the traditional SC (equivalent to α=0) are provided as benchmark setting, but are not part of the full factorial DoE.

(4) The analysis of the IT level, with the two levels defined in the previous section, allows us to determine the value of IT in the different scenarios.

In our full factorial approach, we explore a total of 2 x 3 x 5 x 8 = 240 experimental points. In order to isolate the effects of interest, the rest of model parameters remain fixed in all the simulations. In this regard, it can be highlighted that we adopt a relatively low coefficient of variation for the production pipeline ($L_i cv = 0.1$). That is, we are assuming that this pipeline is generally more stable than the remanufacturing pipeline, given that the quality of raw materials is commonly more homogeneous than the quality of returns and the manufacturing processes can be more easily highly automatised (Abbey and Guide 2018). We set up the rest of model parameters by adopting common values used in similar research works (see *e.g.* Chatfield et al. 2004, Tang and Naim 2004, Cannella et al. 2016, Zhou et al. 2017). A summary of the DoE and model parameters is provided in Table 1.

Table 1. DoE and model parameters.

	Experimental Factors	**Levels**
Information	IT Level (λ)	NIT, EIT
Operation	Remanufacturing Lead time av. ($\mu_{L_{REM}}$)	2, 4, 6
	Remanufacturing Lead time c.v. (L_{REM} c.v.)	0.0, 0.25, 0.50, 0.75, 1
	Return rate (α)	0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8
	Model parameters	**Value**
	Demand average (μ_{D_C})	50
	Demand variance ($\sigma^2_{D_C}$)	20^2
	Manufacturing lead time average (μ_{L_i})	8, $\forall i$
	Manufacturing lead time c.v. (L_i c.v.)	0.1, $\forall i$
	Consumption lead time (L_C)	32
	Review period (R)	1

Safety factor (z)	2
Forecasting period (τ)	15

We performed 20 replications of each experiment, and the simulation outputs were statistically analysed. Total simulation time (T) was set to 4,000 periods to ensure that a steady state of the system is reached. Also, the records of the first 1,000 periods (warm-up time) were disregarded to remove initialisation effects.

3.2 CLSC performance metrics

To evaluate the dynamic performance of the CLSC under study, we employ three classic non-financial performance metrics, namely, Order Variance Ratio ($OVrR$), Inventory Variance Ratio ($IVrR$) and Inventory Average (Iav).

- $OVrR$ measures the amplification of order variability in the SC. $OVrR$ at echelon i is computed as the ratio between the (historical) variance of the orders issued by echelon i and the (historical) variance of Customer demand, see Eq. (7) (Chen et al. 2000, Dejonckheere et al. 2004).
- $IVrR$, firstly proposed by Disney and Towill (2003), assesses the stability of the final position of the serviceable inventory at each period. This metric provides strategic information about the trade-off between the service level achieved and the inventory holding requirements (Ponte et al. 2017). $IVrR$ at echelon i is computed as the ratio between the (historical) inventory variance at echelon i and demand variance, see Eq. (8) (Fu et al. 2015).
- IAv may be associated to the average holding cost over the observation period. It is commonly used in the analysis of production and distribution systems, as it provides concise information on inventory investment requirements (Ganesh et al. 2014, Sy et al. 2017). It is often viewed as a complementary metric to $IVrR$. IAv at echelon i is computed as per Eq. (9).

The three performance metrics have been measured for the three echelons of the CLSC. However, for the sake of clarity, we focus on the results obtained for the most downstream and upstream nodes, *i.e.* the Retailer and the Manufacturer. The former provides information on the operational performance of the Retailer, which is key to determining the inventory performance of the overall SC, as this is the node directly dealing with Customer demand. The latter provides information about the production costs of the SC, also revealing the implications of downstream activities, including remanufacturing, on the upstream dynamic performance. Table 2 summarises all the performance metrics adopted.

Table 2. Performance metrics system.

Performance metrics system			**Key performance metrics for the CLSC**
Order Variance Ratio	$OVrR_i = s^2_{O_i^T}/s^2_{D_C^T}$	(7)	$OVrR_1, OVrR_3$
Inventory Variance Ratio	$IVrR_i = s^2_{I_i^T}/s^2_{D_C^T}$	(8)	$IVrR_1, IVrR_3$
Inventory Average	$IAv_i = \frac{\sum_{t=1}^{T} I_i^t}{T}$	(9)	IAv_1, IAv_3

4 ANALYSIS AND DISCUSSION OF RESULTS

This section presents and discusses the results obtained from the simulations. To determine the statistical impact of the four experimental factors, we conducted Analysis of Variance (ANOVA) tests for each metric using the software SPSS (Version 24).

As previously noted, we conduct a separate analysis of the results obtained by the Retailer and the Manufacturer. For the former, our analysis is structure as follows:

(1) Presenting the results of the ANOVA test.
(2) Comparing both IT levels and evaluating the impact of the three operational factors (*i.e.* mean and variability of the remanufacturing lead time and return rate).
(3) Discussing the interactions between the relevant operational factors separately for each IT level.
(4) Reflecting on the results and summarising the main findings.

For the Manufacturer, we employ the same structure with the exclusion of item (3) since, as we will discuss later, the interactions have a relatively minor impact on the operational performance of this echelon.

4.1 Retailer – Downstream behaviour of the CLSC

4.1.1 ANOVAs

Table 3 displays the ANOVA results (main effects and first-order interactions) for $OVrR_3$, $IVrR_3$, and IAv_3. This table shows that all factors and their first-order interactions are statistically significant at a 95% confidence level (p<0.05) and the three models show a high adjusted R^2. Therefore, in all cases, we reject the null hypothesis that there is no difference of means between groups.

First, we find that the variability of remanufacturing lead times has a significant impact on the Retailer's dynamics. Thus, this factor needs further analysis so as to avoid erroneous estimations of CLSC performance. The other experimental factors also determine the performance of such systems, which is in line with previous studies (see *e.g.* Tang and Naim 2004, Zhou and Disney 2006, Turrisi et al. 2013, Cannella et al. 2016, Zhou et al. 2017).

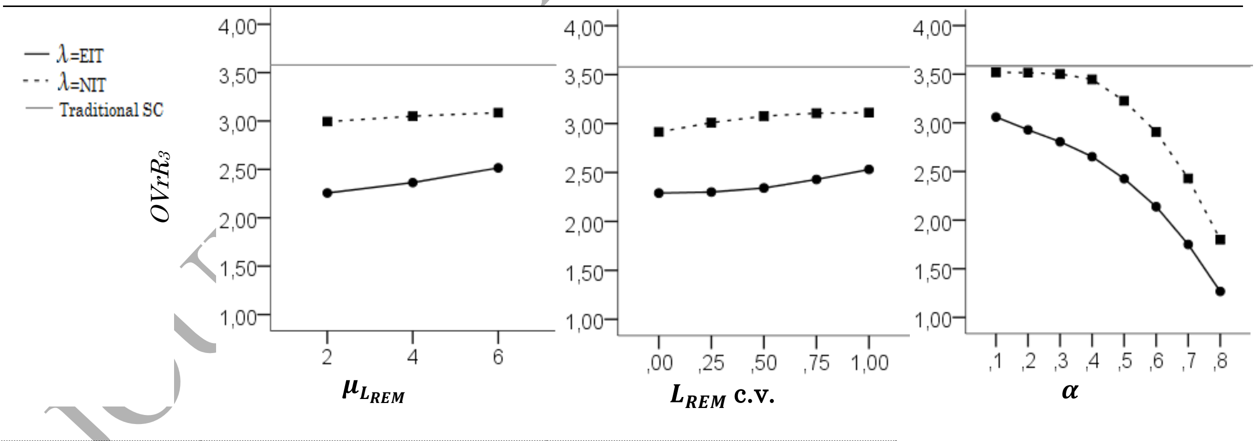
Table 3. Full DoE ANOVA for the Retailer.

Source	***OVrR₃***			***IVrR₃***			***IAv₃***		
	DF	*F*-value	*p*	*DF*	*F*-value	*p*	*DF*	*F*-value	*p*
λ	1	28387.789	<0.001	1	6160.760	<0.001	1	1326.881	<0.001
$\mu_{L_{REM}}$	2	659.313	<0.001	2	420.596	<0.001	2	3267.495	<0.001
L_{REM} c.v.	4	391.168	<0.001	4	652.155	<0.001	4	8022.356	<0.001
α	7	12513.182	<0.001	7	1723.321	<0.001	7	25549.645	<0.001
$\lambda * \mu_{L_{REM}}$	2	157.033	<0.001	2	3.598	0.027	2	1415.207	<0.001
$\lambda * L_{REM}$ c.v.	4	50.554	<0.001	4	7.823	<0.001	4	4356.415	<0.001
$\lambda * \alpha$	7	128.976	<0.001	7	146.365	<0.001	7	437.058	<0.001
$\mu_{L_{REM}} * L_{REM}$ c.v.	8	12.549	<0.001	8	57.880	<0.001	8	288.336	<0.001
$\mu_{L_{REM}} * \alpha$	14	9.453	<0.001	14	21.400	<0.001	14	265.375	<0.001
L_{REM} c.v.* α	28	8.617	<0.001	28	38.151	<0.001	28	604.216	<0.001
	Adjusted R^2 = 96.2%			Adjusted R^2 = 83.8%			Adjusted R^2 = 98.3%		

4.1.2 Remanufacturing operation vs. Information Transparency

Results obtained in the ANOVA suggest that the IT level has a significant impact on the three metrics, indicating that both IT configurations perform very differently. In the following paragraphs, we discuss the impact of the operational factors on Retailer's performance for each IT level. To facilitate this discussion, Figure 2 shows the impact of these factors on the key performance metrics both for λ=*NIT* and λ=EIT. We represent here the average values computed by the ANOVA for the full experimental design. This allows us to obtain a general picture of the problem under analysis, which will be completed later by looking at the interactions between the operational factors.

Overall, our results show that enabling IT has a positive impact on the CLSC. This is in line with prior works, such as Tang and Naim (2004), Hosoda et al. (2005), and Cannella et al. (2016), and extends their findings on the value of SC visibility to closed-loop settings with stochastic remanufacturing lead times. Note that λ=EIT outperforms λ=NIT in all scenarios represented in Figure 2 for $OVrR_3$ and $IVrR_3$. However, it is interesting to note that this figure shows the existence of a region in the parameter space where λ=EIT does not outperforms λ=NIT. This occurs for long and/or highly variable remanufacturing lead times and it manifests itself only from the perspective of IAv_3.



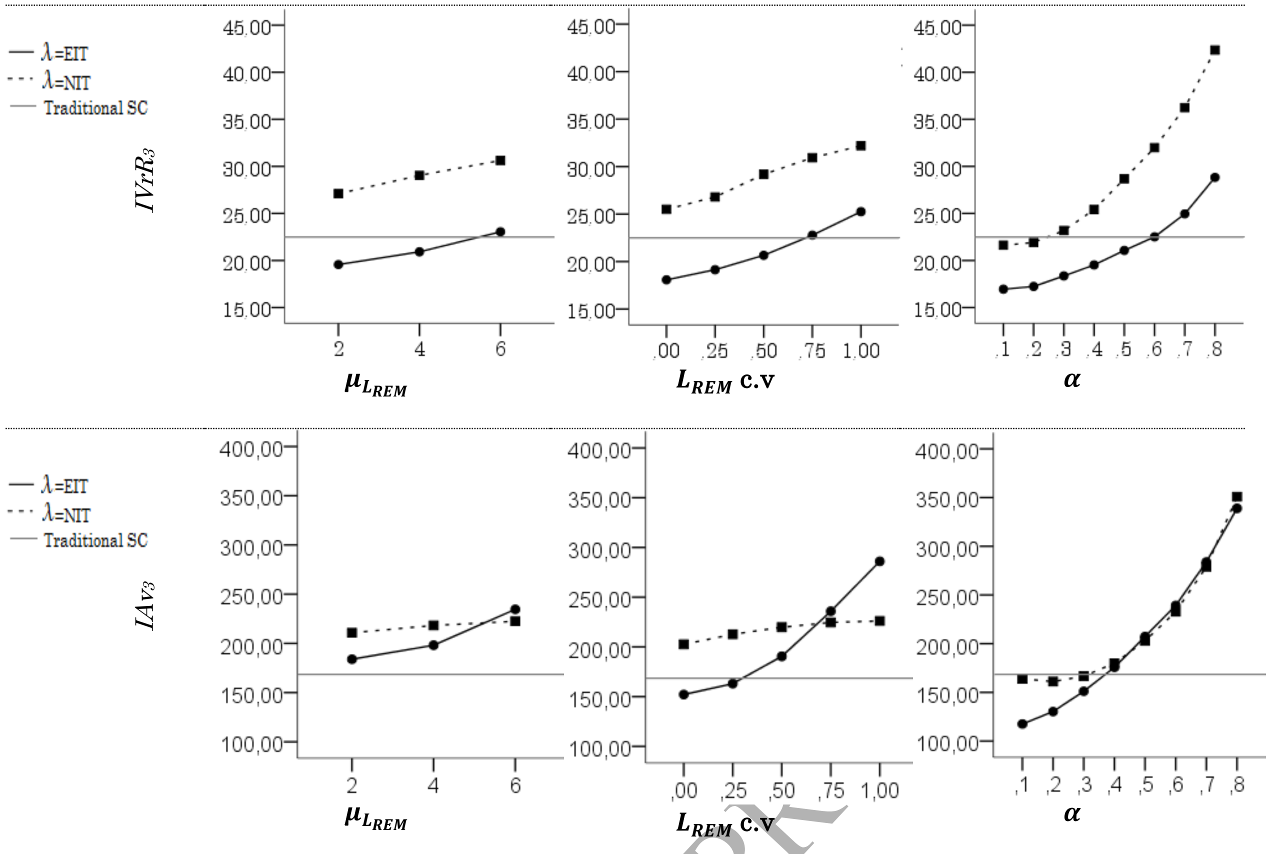


Figure 2. Impact of the operational factors on Retailer's performance for each IT level.

In general terms, increasing the mean and the variability of such lead times, $\mu_{L_{REM}}$ and $L_{REM}\ cv$, significantly undermines Retailer's performance for both IT levels. Under no IT (*λ=NIT*), increasing these factors results in an increased variability of the net demand and thus in higher safety stocks, as per Eq. (3). As a consequence, the difference between the OUT point and the inventory position becomes more volatile and *OVrR₃* grows, while *IAv₃* also increases due to the increase in the safety stock. At the same time, the increased variability in the flow of returns, interacting with a larger order variability, also provokes a higher *IVrR₃*. Under enabled IT (*λ*=EIT), the mechanism for increasing *OVrR₃*, *IVrR₃* and *IAv₃* when $\mu_{L_{REM}}$ and/or L_{REM} c.v. grow is similar. However, it should be noted that the impact on the holding requirements, which becomes visible through IAv_3, is significantly stronger here, since the remanufacturing lead times (both in terms of mean and variability) are explicitly included in the calculation of the OUT level, as per Eq. (4). Indeed, and as previously underlined, for high values of $\mu_{L_{REM}}$ or $L_{REM}\ cv$, the holding costs may be lower for *λ*=NIT than for *λ*=EIT.

We now look at the impact of the return rate α. In line with prior works in the CLSC dynamics literature (see *e.g.* Tang and Naim 2004, Zhou et al. 2017), increasing α reduces $OVrR_3$. This is more significant for λ=EIT (especially for low values of α), since, in this model, α also impacts on the approximation of the pipeline lead time. In contrast, increasing α increases $IVrR_3$ for both IT levels. In terms of $IVrR_3$, this result differs from many studies exploring the impact of the return rate on inventory variability in CLSCs, such as those by Cannella et al. (2016) and Zhou et al. (2017). In this sense, the difference may be explained by the dynamics introduced by the stochastic lead times. That is, while in previous studies the performance of the Manufacturer operates with a decreased inventory variability as this echelon can know the remanufactured products in advance, the consideration of variable lead times makes more difficult to estimate how many remanufactured products will arrive at each period, and thus inventory performance decreases. It can be noted that the Retailer for λ=EIT shows a higher robustness to this detrimental impact of the return rate, since such information is indirectly included in the calculation of the OUT level by considering the WIP of the Remanufacturer. Finally, and consistently with the increase in $IVrR_3$, if α grows, so does IAv_3. This is caused by the higher variability of net demand (which increases with α) for λ=NIT, since this is an important term in the calculation of safety stocks. For λ=EIT, this is not so clear. In fact, by increasing α, the estimated pipeline lead time tends to decrease (since $\mu_{L_{REM}} < \mu_{L_3}$ in our design). Consequently, the OUT level also tends to decrease with α; the extent of this decrease also depends on $L_{REM}\ cv$. Thus, the OUT level does not decrease enough to compensate the increase in the incoming flow of returns, and therefore, as α increases, IAv_3 increases as well. As it can be noticed in Figure 2, IAv_3 is lower for λ=EIT but only if $\alpha \leq 0.4$, being similar to λ=NIT (in average) if $\alpha > 0.4$.

The performance of the traditional, or open-loop, SC is represented in Figure 2 by means of a horizontal grey line. Interestingly, the Retailer achieves a reduced $OVrR_3$ as compared to the traditional setting for both IT scenarios. Looking at the trend of this indicator, only for unusually (very) high values of $\mu_{L_{REM}}$ and/or $L_{REM}\ cv$, $OVrR_3$ may be higher in the CLSC. However, in terms of $IVrR_3$ and IAv_3, the Retailer tends to performs worse in the CLSC than in the traditional SC.

More specifically, and looking at the duration of the remanufacturing process, only for short and stable lead times and in the case of enabled IT (λ=EIT), the CLSC is able to perform better from an inventory perspective (*e.g.* $L_{REM}\ cv \leq 0.5$ in the case of $IVrR_3$, and $L_{REM}\ cv \leq 0.25$ in the case of IAv_3). If we consider the impact of the return rate, the Retailer only performs better than the traditional system for low return rates (*e.g.* $\alpha \leq 0.2$ for λ=NIT or $\alpha \leq 0.6$ for λ=EIT in the case of $IVrR_3$).

4.1.3 Interactions between the operational factors

To provide a more accurate representation of the impact of stochastic lead times on Retailer's performance and to achieve a more comprehensive understanding of the dynamics of CLSCs, we now consider the interactions between the three operational factors (*i.e.* $\mu_{L_{REM}}$ * $L_{REM}\ cv$, $\mu_{L_{REM}}$ * α and $L_{REM}\ cv$ * α). Since both IT levels behave very differently, and to analyse them in detail, we show the interactions separately for each IT level. As previously noted (see Table 3), the three interactions are statistically significant (p<0.05) and they possess high explanatory power (high F-values), especially for IAv_3 and $IVrR_3$.

Figure 3 shows the interaction plots for the two variables defining the remanufacturing lead time, $\mu_{L_{REM}}$ and $L_{REM}\ cv$. Let us first focus on the case where $L_{REM}\ cv$=0 (baseline scenario with deterministic lead times). Looking at the first column (λ=EIT), it can be seen that increasing $\mu_{L_{REM}}$ slightly increases both $OVrR_3$ and IAv_3, while it has marginal impact on $IVrR_3$. By inspecting the second column (λ=NIT), we can observe that increasing $\mu_{L_{REM}}$ has a very small, apparently negative, effect on $OVrR_3$ and IAv_3, and a noticeable, also negative, effect on IAv_3. That is, in the baseline scenario, we observe the 'lead-time paradox' previously documented by some authors and that can manifest itself in different forms; see Hosoda and Disney (2018) for a complete analysis. In our case, we observe that, in the case of no IT, reducing the average remanufacturing lead time decreases the inventory performance of the retailer.

	λ=EIT	λ=NIT

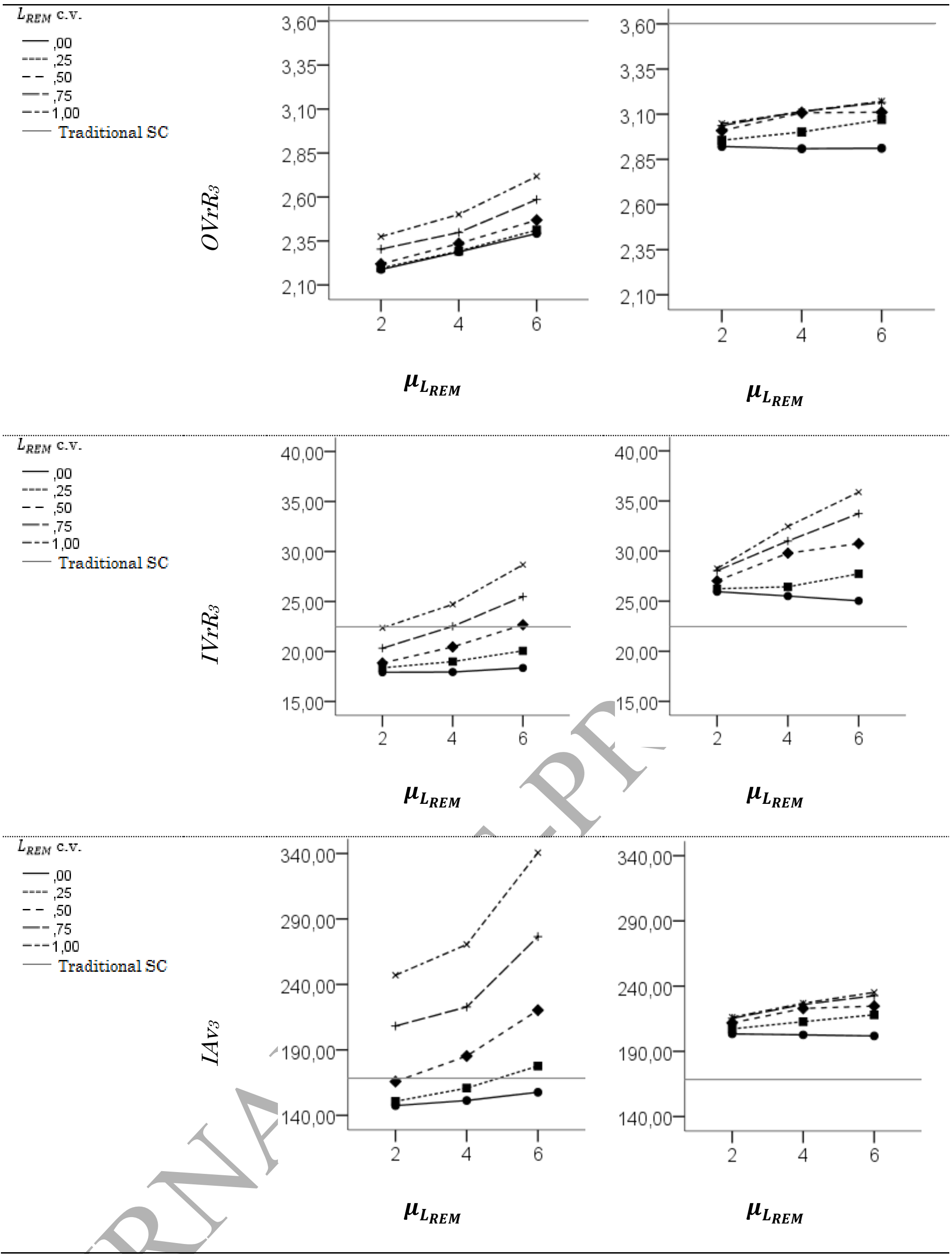


Figure 3. Interaction between lead time average and variability for each IT level.

If we now look at L_{REM} cv>0 (stochastic lead times), one can perceive the strong weight of the interactions. In the case of enabled IT (λ=EIT), as L_{REM} cv grows, the impact of $\mu_{L_{REM}}$ on the three metrics increases, although it can be noted that the increase is more meaningful for $IVrR_3$ and IAv_3 (see the higher slopes of the curves in the first column of Figure 3). That is, the higher the uncertainty (variability) on the remanufacturing lead time, the more sensitive the inventory performance ($IVrR_3$ and IAv_3) of the retailer to changes in the mean of such lead time. Note that, buttressing the discussion in the last paragraph of the previous section, the Retailer here may perform worse in the CLSC than in the traditional SC if the remanufacturing process is characterised by both high mean lead times and high variability. For instance, for $\mu_{L_{REM}} = 6$, $L_{REM}\ cv$ should be lower than 50% such that $IVrR_3$ is lower in the CLSC than in the traditional SC, and for $\mu_{L_{REM}} = 4$ this limitation can be relaxed to $L_{REM}\ cv$<0.75. This becomes even more restrictive for IAv_3, as only for relatively short and stable remanufacturing lead times the CLSC performs better; *e.g.* if $L_{REM}\ cv$=0.25, $\mu_{L_{REM}}$ needs to be no longer than 4.

In the case of no IT (λ=NIT), we notice that the 'lead-time paradox', previously observed for $L_{REM}\ cv$=0 from the perspective of $IVrR_3$, disappears when there is stochasticity in the remanufacturing process. Note that, if $L_{REM}\ cv \geq$0.25, reducing the mean of remanufacturing lead times always have a positive effect on inventory variability. In this sense, variability in the remanufacturing lead times transforms the dynamics of CLSCs, challenging the validity of relevant insights in the baseline scenario. Finally, we highlight that while shortening remanufacturing lead times has no benefit in terms of $OVrR_3$ and IAv_3 for $L_{REM}\ cv$=0, it improves the dynamic performance of the CLSC with stochastic lead times, which again underlines the relevance of such interactions in the dynamics of CLSCs.

A final observation that can be made is that the average net stock is much more sensitive to the mean and variability of remanufacturing lead times in the case of enabled IT (λ=EIT) than in that of no IT (λ=NIT). Note that in the first case it varies approximately between 140 and 340, while in the latter it is constrained to the interval 200-240. This can be easily interpreted from the perspective that enabling IT results in that information on the remanufacturing process is being used within the ordering policy. This allows us to understand why $IVrR_3$ may be higher or lower in λ=EIT than in λ=NIT, mainly depending on $L_{REM}\ cv$.

Figure 4 displays the interaction plots for $\mu_{L_{REM}} * \alpha$. It shows that the impact of α on Retailer's performance is conditioned by $\mu_{L_{REM}}$, especially for λ=EIT. As pointed out before, under λ=EIT, increasing $\mu_{L_{REM}}$ in the presence of lead time variability tends to deteriorates the Retailer's performance, as the WIP of remanufactured products and the estimated pipeline lead time become more variable (and such information is explicitly included in the OUT policy). Therefore, increasing α amplifies this detrimental effect, since it increases the variability of both the WIP and the estimate of the pipeline lead time.

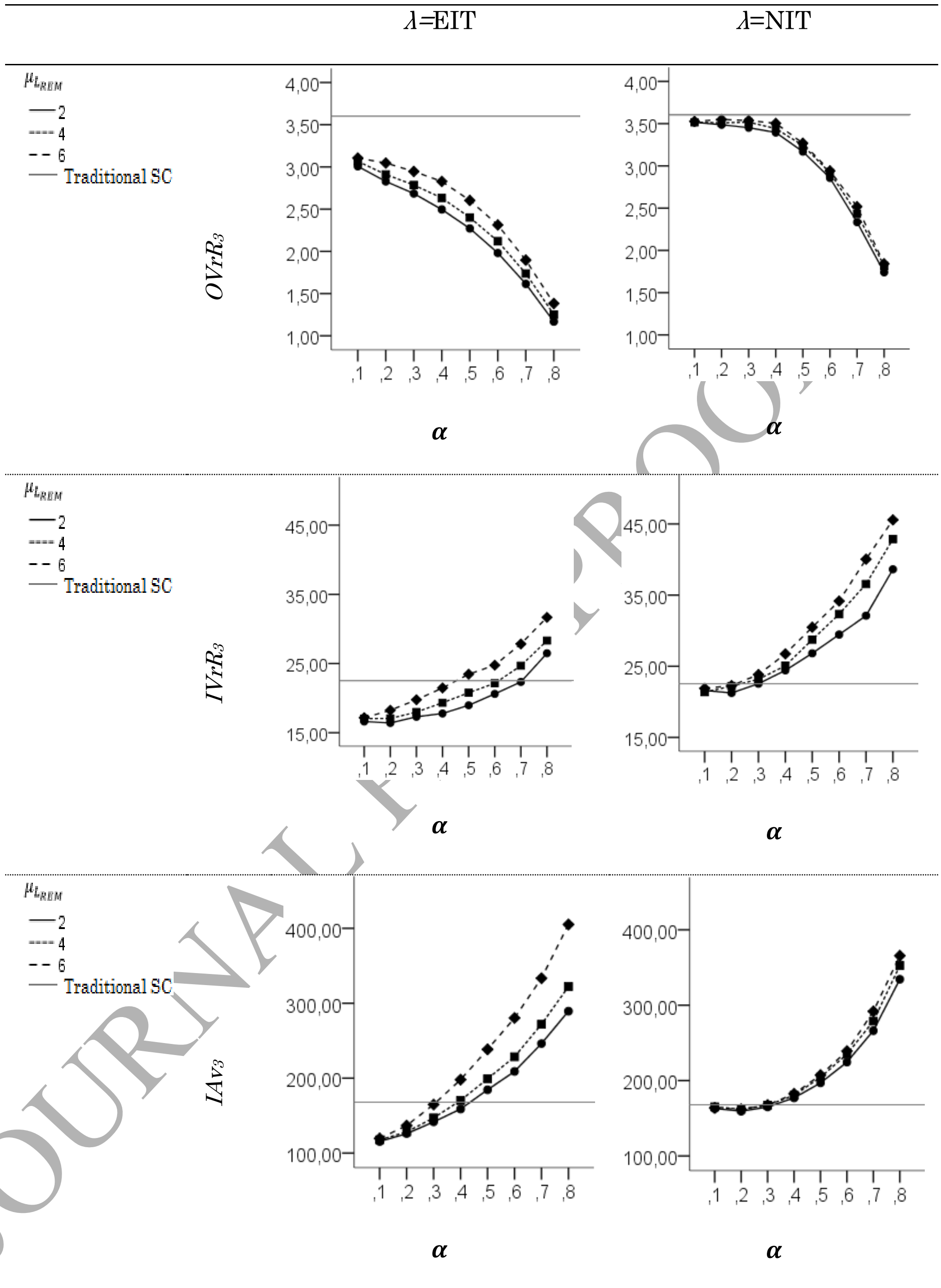


Figure 4. Interaction between lead time average and return rate for each IT level.

A noteworthy consequence of this interaction is that increasing $\mu_{L_{REM}}$ restricts the interval of α in which the Retailer performs better in the CLSC than in the traditional SC; *e.g.* for $IVrR_3$ this interval is $\alpha \leq 0.7$ when $\mu_{L_{REM}}$=2 but it is restricted to $\alpha \leq 0.4$ when $\mu_{L_{REM}}$=6. Another interesting consequence of a high $\mu_{L_{REM}}$ is that as α increases, IAv_3 can be higher for λ=EIT than for λ=NIT. For instance, when $\mu_{L_{REM}}$=6, IAv_3 is higher for λ=EIT than for λ=NIT when $\alpha \geq 0.4$.

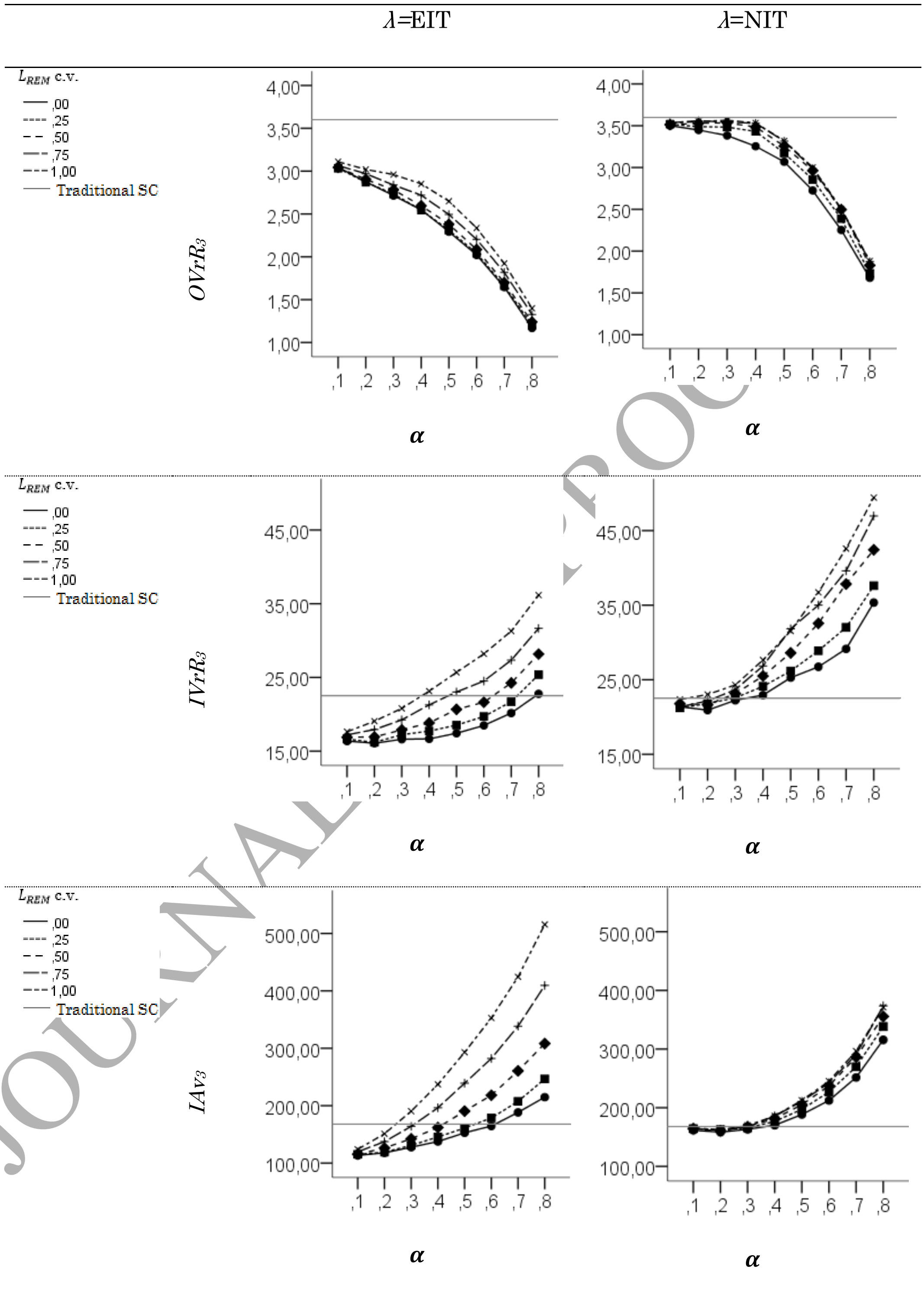


Figure 5. Interaction between lead time variability and return rate for each IT level.

Finally, Figure 5 shows the interaction plots for $L_{REM}\,cv * \alpha$. Again, the relation between α and CLSC performance significantly depends on $L_{REM}\,cv$ for λ=NIT and λ=EIT, especially in the latter scenario. Note that increasing α when there is high $L_{REM}\, cv$ results in an increased variability of Remanufacturer's WIP and overall pipeline lead time.

This interaction is particularly important for $IVrR_3$ and IAv_3. Notice that, when $L_{REM}\, cv$=0 and for λ=EIT, $IVrR_3$ is lower than or equal to the benchmark obtained for the traditional SC for $\alpha \leq$0.8, while in case of $L_{REM}\, cv$=1.0 this is only true only for $\alpha \leq$0.4. For IAv_3 and $L_{REM}\, cv$=1.0, the above would only be true for $\alpha \leq$0.2. Despite this important interaction, λ=EIT outperforms λ=NIT in terms of $OVrR_3$ and $IVrR_3$ even for high $L_{REM}\, cv$ and α. However, this is not the case for IAv_3, where λ=EIT performs worse than λ=NIT for high values of $L_{REM}\, cv$ and α.

4.1.4 Summary of findings for the Retailer

On the basis of the above reported observations on the downstream behaviour of the CLSC under consideration, we elaborate the following five main findings:

1. *The variability of remanufacturing lead times significantly undermines Retailer's dynamic behaviour, especially from the perspective of a decreased inventory performance; and ignoring the uncertainty associated to that process nearly always results in an overestimation of CLSC performance.*
2. *Enabling information transparency in the CLSC (by sharing relevant information on the remanufacturing process) smooths the orders issued by the Retailer and improves the stability of the serviceable inventory; however, under some circumstances, this may increase the safety stock requirements and hence the holding costs.*
3. *In terms of order variability, a Retailer in a CLSC always outperforms the same Retailer operating in a traditional SC, while in terms of inventory variability and average stock there is a relatively small region (in general terms, for short and stable lead times and low return rate) in which the performance of a Retailer operating in a CLSC is better.*
4. *Decreasing the average remanufacturing lead time…*
    a. *Under no IT, it has a negative impact on Retailer's inventory performance for fixed lead times —a 'lead-time paradox'. However,*

this counterintuitive effect cannot be observed for variable lead times, where shortening lead times has always a positive effect.

b. *Under enabled IT, it has a slightly positive impact on Retailer's performance for fixed lead times. Having noted that, reducing mean lead times becomes much more important in the presence of variability in such lead times.*

5. *In general terms, increasing the volume of returns has a positive impact on Retailer's order variability but a negative impact on inventory variability. The strength, but not the direction, of the such consequences of increasing return rates on Retailer's performance are significantly altered by the mean and variability of remanufacturing lead times, especially with enabled IT. As a general rule, Retailer's performance is much more sensitive to changes in the return rate for long and variable lead times.*

4.2 Manufacturer – Upstream behaviour of the CLSC

4.2.1 ANOVAs

Table 5 provides the ANOVA results for $OVrR_1$, $IVrR_1$, and IAv_1. Again, all the analysed factors are statistically significant at a 95% confidence level (p<0.05), thus finding evidences to reject the null hypothesis (no difference in means between groups). This suggests that, in the considered multi-echelon CLSC, the remanufacturing process significantly impacts on Manufacturer's dynamics.

Table 5. Full DoE ANOVA for the Manufacturer.

Source	***OVrR₁***			***IVrR₁***			***IAv₁***		
	DF	*F*-value	*p*	*DF*	*F*-value	*p*	*DF*	*F*-value	*p*
λ	1	3838.358	<0.001	1	3071.712	<0.001	1	6694.060	<0.001
$\mu_{L_{REM}}$	2	78.292	<0.001	2	80.607	<0.001	2	191.798	<0.001
L_{REM} c.v.	4	42.036	<0.001	4	65.231	<0.001	4	154.640	<0.001
α	7	3402.961	<0.001	7	85.282	<0.001	7	501.592	<0.001
$\lambda * \mu_{L_{REM}}$	2	24.103	<0.001	2	25.444	<0.001	2	68.362	<0.001
$\lambda * L_{REM}$ c.v.	4	7.507	<0.001	4	5.559	<0.001	4	7.414	<0.001
$\lambda * \alpha$	7	19.581	<0.001	7	43.583	<0.001	7	177.071	<0.001
$\mu_{L_{REM}} * L_{REM}$ c.v.	8	2.000	0.043	8	4.798	<0.001	8	7.958	<0.001

$\mu_{L_{REM}}$ $*\alpha$	14	1.784	0.045	14	2.647	0.002	14	8.151	<0.001
L_{REM} c.v. * α	28	1.804	0.010	28	3.170	<0.001	28	8.106	<0.001
	Adjusted R^2 = 85.5%			Adjusted R^2 = 51.4%			Adjusted R^2 = 74.5%		

As for the Retailer, the high F-values observed for λ indicates that the IT level has a high impact on the three metrics. Nevertheless, looking at the models' adjusted R^2 we underline that this impact is significantly lower than that on Retailer's performance, since the observed performance variations are less explained by the variations in the experimental factors. The reason behind this may be that, as per Figure 1, the flow of returns joins the forward flow of materials at the Retailer level; hence, variations in such parameters can be expected to have less impact on the Manufacturer's operation and performance than in the Retailer's.

4.2.2 Remanufacturing operation vs. Information Transparency

Figure 6 visualises the effect of the three operational factors on the dynamics of the Manufacturer for each IT level. First, it can be seen that this SC echelon performs significantly better under λ=EIT in all cases. Thus, the value of IT, via visibility on the remanufacturing process, for enhancing CLSC dynamics not only impacts the node who receives the returns, but also the upstream SC nodes.

Importantly, Figure 6 clearly shows the benefits derived from reducing and stabilising remanufacturing lead times, *i.e.* decreasing $\mu_{L_{REM}}$ and $L_{REM}\,cv$, on Manufacturer's performance. Furthermore, this performance improvement can be more significant in relative terms for λ=EIT. Regarding the return rate, increasing α also reduces $OVrR_1$, showing a similar behaviour for both IT levels. However, contrarily to the Retailer, an increase in α may also reduce $IVrR_1$. Notice that $IVrR_1$ monotonously decreases as α grows under λ=EIT. For λ=NIT, this decrease is observed only for high values of α ($\alpha \geq 0.6$). Finally, we note that the average position of the Manufacturers' inventory, IAv_1, strongly increases with α, being the slope significantly more pronounced for λ=NIT.

We now compare the performance of the Manufacturer with that in the traditional, open-loop SC setting (which is represented by a horizontal grey line). As a general rule, the Manufacturer performs significantly better in the CLSC. Note that $OVrR_1$ and $IVrR_1$ are lower than in the traditional SC under both IT levels for all the scenarios. This improvement may be explained as a consequence of the $OVrR_3$ decrease. In other words, the upstream SC nodes significantly benefit from closing the loop, even when this happens at downstream levels, as a consequence of the manufacturer issuing smoother orders. Having said that, in terms of IAv_1 the improvement happens only under λ=EIT, except if the remanufacturing lead times are long and variable ($\mu_{L_{REM}}/\mu_{L_3}$>0.75, L_{REM} cv>1), or the return rate is high (α>0.7).

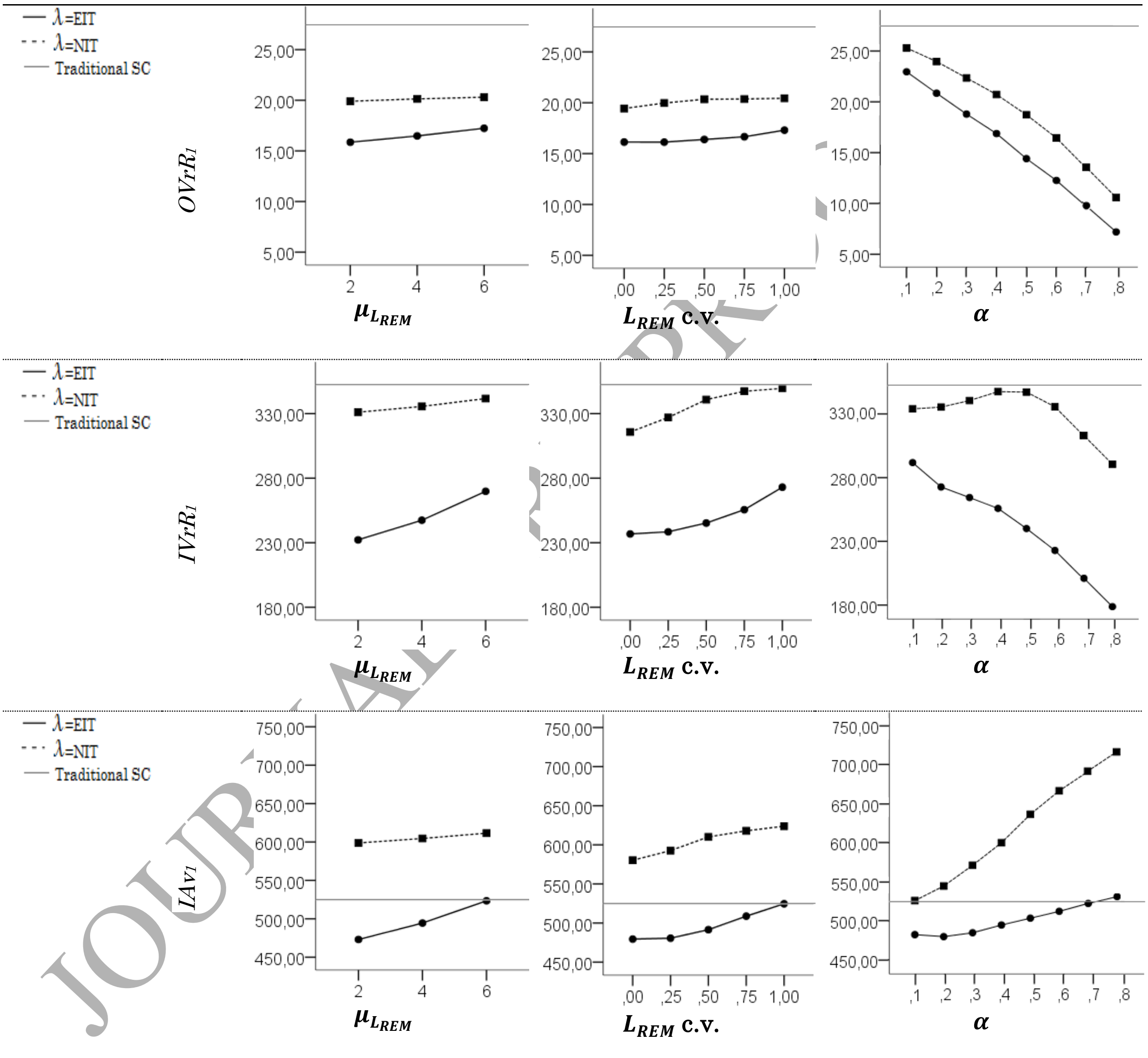


Figure 6. Impact of the operational factors on Manufacturer's performance for each IT level.

Finally, we note that we have also analysed the interactions between the operational factors for the Manufacturer. Results reveal that these interactions are not significant for no IT (λ=NIT), while they have a very low impact on Manufacturer's performance in the case of enabled IT (λ=EIT). That is, while the main effects of the downstream factors are significant for the Manufacturer, the impact of such interactions are not transmitted upstream. For this reason, as previously discussed, we do not report the interactions for the Manufacturer.

4.2.3 Summary of findings for the Manufacturer

On the basis of the previous analysis of the behaviour of the Manufacturer, we present the following three main findings:

1. *Both the mean and the variability of remanufacturing lead times greatly damage the operational performance of the Manufacturer in CLSCs, through an increased order and inventory variability as well as higher inventory requirements.*
2. *Enabling downstream information transparency improves Manufacturer's dynamic performance. In addition, it allows the Manufacturer to obtain significant benefits from increased return rates in the form of reduced order and inventory variability. However, there might be a slightly increase in the average inventory.*
3. *Even though the SC is closed at the lowest echelon, i.e. the Retailer, the Manufacturer significantly benefits as compared to traditional settings. Both order and inventory variability decrease at the Manufacturer level, regardless the information transparency scheme; however, the average inventory tends to increase if there is no IT.*

5 SUMMARY OF MANAGERIAL INSIGHTS

In this section, we derive some managerial insights that can be useful for CLSC managers, particularly if their CLSCs have similarities with the structure and typology we have investigated. In this regard, we highlight three assumptions: (i) remanufactured products enter at the Retailer level; (ii) both manufactured and remanufactured products can be utilised to meet the customers' demand, *i.e.* perfect substitution; and (iii) remanufacturing processes are characterised by some degree of variability, probably due to the uncertain nature of the quality of the returns. Like in the previous section, we discuss the managerial insights separately for retailers and manufacturers operating in CLSCs.

5.1 Implications for Retailers

Firstly, we note that in the analysed CLSC the Retailer benefits from smoothed orders in comparison with traditional SCs. In this sense, since increasing the return rate diminishes order variability, retailers have a motivation for pursuing an increase in the volume of returns. This dynamic improvement is, however, conditioned by the length and stability of remanufacturing lead times and by the adopted IT level. In fact, while the Retailer's order variability decreases for both levels of IT, this reduction is more significant for the enabled IT scenario.

In terms of inventory performance, enabling IT turns out to be crucial. Under no IT, the Retailer would slightly benefit from including the collection and restoring processes in the SC if and only if the process is characterised by very low return rates and a very short and stable remanufacturing lead times. However, under enabled IT, the Retailer will see its inventory performance substantially improved as compared to the traditional SC. In this way, the Retailer strongly benefits from a close collaboration with the Remanufacturer by obtaining real-time information about its current WIP and lead times and by incorporating this information into its own order policy. Nevertheless, such benefits are also conditioned by the efficiency and stability of the remanufacturing process. In this regard, it is again extremely important to reduce the variability of the remanufacturing process as much as possible, especially when remanufacturing lead times are high and/or when there is a high volume of returns. In fact, the negative impact of long remanufacturing lead times on Retailer's inventory performance is relatively low when such lead times are stable. On the contrary, volatile remanufacturing lead times have a greater detrimental impact on Retailer's inventory performance. As an example, if the remanufacturing lead time is around 50% of the Retailer's lead time, the Retailer can benefit from a 20% less inventory variability with respect to the open-loop system if lead times are stable. However, if the coefficient of variation of remanufacturing lead times is ~75%, this benefit would be null. This is even more restrictive for average stocks (*e.g.* the same Retailer would have reduced average stocks only if the coefficient of variation is below ~25%).

Essentially, if there is high variability in the remanufacturing process, the flow of incoming remanufactured products at the Retailer will be also characterised by an elevated inconstancy, resulting in higher inventory variability and average stock. As the return rate increases, the amount of incoming remanufactured products increases and the impact of such inconstancy on Retailer's inventory performance is more pronounced. As an example, in a perfectly stable remanufacturing process, the Retailer can benefit from reduced inventory variability for return rates up to 80% of the average demand, and from reduced average stock for return rates up to 60% of the average demand. However, these percentages drastically diminish when there is variability in the remanufacturing process.

Finally, if the remanufacturing process is characterised by high and very variable lead times (*e.g.* mean remanufacturing lead time over 75% of the average Retailer's lead time, and a coefficient of variation of this lead time over 75%) and an average-to-high volume of returns (*e.g.* over 30% of the average demand), enabling IT may lead to erroneous estimations of the placed orders due to overestimations of the safety stocks, resulting thus in higher average stocks. However, the Retailer still benefits in terms of order and inventory variability, and therefore, managers need to consider the trade-off between reduced costs associated with order and inventory variability and increased costs associated with average stocks when deciding which IT level should be adopted.

5.2 Implications for Manufacturers

In CLSCs, the upstream members' dynamics may also be strongly affected by remanufacturing process taking place at downstream levels. In fact, the lower Retailer's performance caused by the variability in the remanufacturing process is transmitted upstream and it also has negative consequences on Manufacturer's inventory variability and average stocks. Nonetheless, contrarily to the Retailer, the Manufacturer benefits from a reduced variability in both orders and inventory in the CLSC (as compared to the open-loop SC) for a wide range of scenarios. Specifically, such benefits are substantially higher when IT is enabled. In terms of average stock, the Manufacturer exclusively benefits in the case of enabled IT. Therefore, the Manufacturer is encouraged to work in close collaboration with the Retailer to reduce remanufacturing lead time variability and to promote IT.

Assuming an enabled IT scenario, as the return rate increases, the Manufacturer significantly benefits from the perspective of order and inventory variabilities, while the average stock marginally increases. Therefore, excluding other economic implications (such as that related to direct sales), the Manufacturer in a CLSC should try to promote a high recollection of used products, even if there is an important variability in the quality of returns (the negative impact of remanufacturing lead time variability is lower than the positive impact of returns). As an example, if 70% of the average customer demand is returned to the SC, the Manufacturer may have its order (inventory) variability reduced by 64.77% (43%) with respect to the open-loop SC, while the average stock may stay as in the traditional system. On the contrary, increasing the return rate when there is no IT may dramatically increase Manufacturer's average stock.

5.3 Summary of implications for the CLSC

To sum up, it is important to highlight that while the Manufacturer significantly benefits from high return rates and enabled IT, such conditions only reward the Retailer in case of short and stable remanufacturing lead times. Therefore, in order to incentivise the Retailer to make use of the information on the Remanufacturing process and to pursue high return rates, the SC partners need to join efforts to improve the reverse flow of materials.

There are three main avenues for managers to achieve said target:

(1) *Technology / process driven.* Remanufacturing lead times may be shortened and stabilised by investing in technology to process returns in a more effective and efficient manner (Zhou et al. 2017). This would allow managers to improve the flexibility of the remanufacturing process so as to absorb the uncertainty in the quality of returns.

(2) *Quality driven.* There are several mechanisms that may help to reduce variations in the quality of returns, as well as to improve their average quality —which would result in a reduced lead time variability and in a

decreased mean, respectively. Following the discussion by Goltsos et al. (2018), we make a distinction between passive and active mechanisms.

a. *Passive – Quality grading* of the incoming returns (*i.e.* classifying returns according to their quality as soon as they reach the remanufacturing facilities). Using different remanufacturing lines for each grade would allow to reduce the uncertainty associated to the processing times on each line.

b. *Active – Controlling the quality* of returns through incentives for customers to return the products after a certain consumption time. This is expected to result in an improved mean quality, as it would reduce the time deterioration of the products.

(3) *Location driven*. As previously discussed, the remanufacturing lead time in our model includes both the reprocessing time and the transportation from the Remanufacturer to the Retailer. In this sense, redesigning the logistic network by placing the Remanufacturer closer to the Retailer's position would have a significant value for improving the dynamics of CLSCs, as it would facilitate a reduction in the mean and variability of the relevant lead times in the reverse flow of materials.

6 FINAL REMARKS, LIMITATIONS, AND FUTURE RESEARCH

This research has investigated the dynamic behaviour and operational performance of CLSCs characterised by variability in the remanufacturing lead times, which has received very little attention in prior literature despite this variability being one of the defining features of CLSCs in practice. We have considered not only how this variability impact on the CLSC but also how this affects established knowledge for CLSCs with deterministic remanufacturing lead times.

We have observed that, as a general rule, ignoring that uncertainty associated to the reverse flow of materials results in an overestimation, usually pronounced, of CLSC performance. This emphasises the need for incorporating this feature into the modelling assumptions in CLSC studies with the aim of understanding better the dynamics of such relevant systems.

In line with prior studies, we have found that the Bullwhip Effect is generally reduced in CLSC settings. This holds even for long and variable remanufacturing lead times. However, inventory dynamics of CLSCs may significantly suffer from such conditions. Under these circumstances, the inventory performance of CLSCs is generally lower than in traditional systems due to the presence of uncertainty both in the forward and in the reverse flow of materials, which do not generally occur when we only consider uncertainty in the forward flow of materials.

A noticeable observation in the CLSC literature is the so-called 'lead-time paradox', according to which CLSCs may benefit from an increase in the remanufacturing lead time. Interestingly, we observe that CLSCs with variable lead times are much less likely to experience this paradox. While we have also seen this paradox in our study for fixed lead times, this counterintuitive effect disappears as variability in the remanufacturing lead time grows. Therefore, such variability always places a monetary value on shortening lead times, which may not happen in traditional SCs. The opposite impact of the mean lead time on deterministic and stochastic scenarios also underlines the complexity of the dynamics of such systems.

In a CLSC in which the remanufactured products enter the forward flow of materials at the lowest echelon, our results show that all the SC echelons benefit from enabling IT between that level and the Remanufacturer. Indeed, the upper echelons benefit more from IT, even though they do not directly participate in the sharing of information. This underscores the need for aligning incentives in the SC in order to motivate the lower echelons to share the relevant information, as it would allow to improve the dynamic performance of the CLSC.

Our paper is limited by the different assumptions that we have made. One of them is the adoption of well-known OUT policies. In our study, these rules have offered a decreased inventory performance for high volumes of returns and/or long and variable remanufacturing lead times. This perspective poses new directions for future research, since these policies, in their traditional forms, are not able to deal efficiently with the stochasticity of returns and lead times.

Therefore, future research is required to improve the order policies so as to deal with such stochasticity in a better way; *e.g.* exploring other policies such as the 'Proportional-Order-Up-To' model (Disney and Lambrecht 2008, Braz et al. 2018), developing ad-hoc inventory policies, or developing analytical models to infer optimum policies.

Moreover, as noted before, we have studied an OUT replenishment rule that does not incorporate crossover information. The use of such information may be an effective means for improving SC performance, as discussed in prior works, such as Robinson et al. (2001) and Chatfield and Pritchard (2018). In light of this, exploring how information about order crossovers may be employed for improving the dynamics of the CLSC also defines a promising area for future research. Likewise, it would be interesting to explore the development of improved OUT policies for scenarios in which information cannot be shared that are based on estimations on the flow of returns when lead times are stochastic.

Finally, it is important to underline that our work considers that remanufactured products can be utilised to satisfy the demand of end customers. While this is the case of several practical settings, such as spare parts industries, in other CLSC scenarios the assumption of perfect substitution may not hold due to customers valuing differently new and remanufactured products. The exploration of such systems is also a research avenue worth pursuing. Note that in this case an interesting problem of market segmentation emerges, as the demand of new and remanufactured products, with different prices, may be strongly correlated.

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